CHAPTER 19 –Intelligent Creativity Support

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Introduction

We present an argument for the advancement of Intelligent Creativity Support (ICS) systems as an integrating framework for ITSs, affective computing, and creativity support tools, in a manner that closely aligns each of these technologies and research agendas with the componential model of creativity, i.e., domain-relevant expertise, intrinsic motivation, and creative thinking style. We also present strategies for developing and evaluating student models for the just-in-time assessment of creativity.

While there are over one hundred definitions of creativity (Amabile, Barsade, Mueller & Staw, 2005), there is consensus that it entails a product, idea, or process that is novel and useful (Mayer, 1999). Creativity is at the core of all societal advancements. However, it is also present "not only when great historical works are born but also whenever a person imagines, combines, alters, and creates something new, no matter how small" (Vygotsky, 2004).

Creativity has been described as the most vital economic resource of our time (Florida, 2002; Kaufman & Beghetto, 2009) and the U.S. Council on Competitiveness has indicated that it will be the top factor determining America's success in the 21st century (Robbins & Kegley, 2010; Wince-Smith, 2006). Thus, understanding how to foster creativity skills is a crucial societal goal (Tripathi & Burleson, 2012). U.S. universities, colleges, and K–12 school systems can play a fundamental role in producing an innovative and creative workforce, by helping students develop such skills (Robbins & Kegley, 2010; Vance, 2007; Wince-Smith, 2006). Indeed, the 21st Century Skills initiative (Trilling & Fadel, 2009) and Common Core Standards (NGA & CCSSO, 2012) call for teaching creativity, innovation, and deep problem-solving abilities.

Unfortunately, various challenges have hindered the adoption of creativity instruction and practices in traditional classrooms (McCorkle, Payan, Reardon & Kling, 2007). For one, few teachers have been trained in how to teach creativity (Mack, 1987). More importantly, classroom settings do not enable teachers to provide the individualized support needed for effective creativity facilitation. In particular, while personalized instruction has tremendous potential to improve student learning (Cohen, Kulik & Kulik, 1982; Lepper, 1988), affect (motivation and emotion) (Lepper, 1988; Picard, 1997), and metacognitive skills (Bielaczyc, Pirolli & Brown, 1995), providing a human tutor for each student is simply not practical. Given these challenges, most of the work thus far reflects anecdotal, descriptive data (Ma, 2006; Robbins & Kegley, 2010; Runco, 2004; Scott, Leritz & Mumford, 2004), although some exceptions exist (Cheung, Roskams & Fisher, 2006; Clapham, 1997; Dewett & Gruys, 2007).

Since ITSs can provide large-scale instruction that continuously adapts to learners' needs (Aleven, McLaren, Roll & Koedinger, 2006; Arroyo, Cooper, Burleson, Muldner & Christopherson, 2009; Koedinger, Anderson, Hadley & Mark, 1997; Self, 1998; VanLehn et al., 2005), they present a unique opportunity to address issues associated with teaching creativity. ITSs have already successfully improved domain learning by tracking students' problem-solving progress, providing tailored help and feedback, and selecting appropriate problems (Shute & Psotka, 1996; VanLehn et al., 2005). However, ITS have also been criticized for over-constraining student problem solving and over-emphasizing shallow procedural knowledge, and therefore not properly addressing 21st century higher-order skills like critical thinking and creativity (Trilling & Fadel, 2009).

We present strategies for designing a ICS system to foster student creativity during Science, Technology, Engineering and Mathematics (STEM) activities. The ICS framework is situated within Amabile's validated and broadly adopted componential model of creativity (1983). Amabile's model highlights three factors within an individual that are needed for creativity: domain knowledge, motivation, and creative thinking styles. Moreover, Amabile and others have demonstrated that positive affect contributes to creative problem solving (Isen, 2004; Isen, Daubman & Nowicki, 1987), leading to increased intrinsic motivation, deeper exploration, and more appropriate outcomes or solutions. Our goal is to have ICS integrate and leverage traditionally isolated technological components that are critical to advancing a student's creative capacity (Figure 19-1): (1) domain relevant knowledge supported by ITS; (2) affect (motivation and emotion) fostered by Affective Learning Companions (ALCs); and (3) creative thinking skills scaffolded by Creativity Support Tools (CSTs). The ICS design can also implicitly account for external factors that influence creativity, such as evaluation and time pressure (Amabile, 1983; Amabile et al., 2005). The ultimate goal of the ICS strategy is to extend traditional ITS instruction with personalized affective support and metacognitive creativity training to improve creativity and learning outcomes.

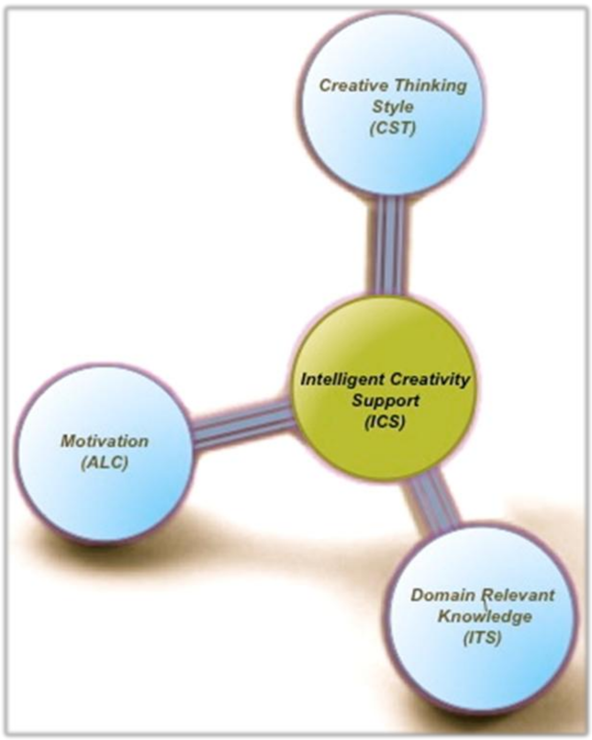

Figure 19-1. Advancing a new class of cyberlearning technologies, ICS will integrate personalized support with Amabile's componential model of creativity. ICS will combine ITSs to increase domain relevant knowledge; ALCs to foster motivation; and CSTs to advance creative thinking styles.

Student Models for Just-In-Time Assesment

To provide creativity support tailored to a given student's needs, an ICS requires a *student model* (VanLehn, 1988) that assesses students' attributes relevant to creativity processes and outcomes throughout their educational activities. To prepare to conduct this research, we have taken steps in this direction through related work searches that have highlighted a preliminary set of attributes that we will take into account and extend as needed. These attributes are encapsulated by Amabile's componential model of creativity and related research as follows:

Domain-Relevant Knowledge. Amabile (1983) shows that the more one knows, the more opportunities there are for creativity, something the ICS student model needs to account for in its assessment of a student's creativity. Also related to the assessment of creativity is the fact that its very definition involves the production of a novel idea or problem-solving step – the most natural way for a model to determine novelty is whether the student already possessed the knowledge related to the idea or step or if it was constructed on the spot.

Affect (Motivation and Emotion). How students feel greatly influences the creativity process and its outcomes. Thus, the ICS model will rely on the data from affective sensing devices as well as tutor variables to assess states like intrinsic motivation, central to Amabile's theory (Amabile, 1983), as well as other affective states such as frustration (e.g., indicating Stuck!) and flow.

Metacognition Related to Creative Thinking Styles. The third element of Amabile's theory pertains to what she terms as "creative thinking style," such as how flexible and imaginative people are in their approach to problems, indicating the metacognitive skills required for creativity.

The ICS creativity student model will represent and infer information related to these three attributes. For the modeling of knowledge and metacognition, we will build student models via established techniques (e.g., Conati, Gertner & VanLehn, 2002; Corbett, McLaughlin & Scarpinatto, 2000; Mitrovic, 2012; Reye, 2004) for modeling of these attributes. Specifically, we will use cognitive and metacognitive task analysis to identify fine-grained skills needed to solve a problem (*knowledge*) and for creativity in general (*metacognition*, including, for instance, divergent thinking). These skills can be computationally represented using a *rule-based* approach that enables the system to automatically model both the target solutions and skills sets (Anderson, 1993). This is accomplished by tying parameters to each rule to represent the probability that the student knows the corresponding skill, which "fire" when a certain threshold is exceeded. In addition, this approach can be used to provide the backbone of a Bayesian network that makes the structure of the student knowledge and metacognitive skills explicit, as in (Conati et al., 2002). Overall, this probabilistic approach has the advantage of recognizing that modeling student knowledge and metacognition is not a black and white process, since there is typically inherent uncertainty arising from, for instance, student slips and guesses (Reye, 2004) and/or lack of direct evidence on student state of interest (e.g., divergent thinking).

For the modeling of affect, initially, we will refine our existing student models developed in our work (e.g., Arroyo et al., 2009) and use their output as inputs to the ICS creativity model. These models already capture attributes that are relevant to the research at hand (e.g., interest, related to intrinsic motivation and Flow, frustration) by relying on data from the sensing devices and tutor variables. However, as mentioned above, these models do not take into account the uncertainty inherent in assessing affect as other existing affective models do (e.g., Conati & Maclaren, 2009) and so we will extend and/or redesign them as needed.

In order to calibrate the main ICS creativity model, as well as its knowledge, affect, and meta-cognition sub-models, we will conduct empirical studies to collect data from students (high school and college) as they interact with the target tutor while a target set of sensors captures their physiological responses. The goal behind these evaluations will be to collect a rich data set that enable us to (1) evaluate the accuracy of the student models for capturing the target student attributes and (2) analyze how student actions and student affect influence the creative process during open-ended problem solving.

Model Accuracy: To determine student model accuracy we will compare model output to a gold standard (Arroyo et al., 2009; D'Mello & Graesser, 2012; Muldner, Burleson & VanLehn, 2010). In the case of student knowledge, this gold standard is typically a test targeting the domain concepts. For affect and metacognition, the situation is more complicated since information on students' feelings and high-level thoughts is not readily available. Thus, we will use a two-prong approach that we have relied on in the past: (1) talk-aloud protocol by having students verbalize their thoughts and feelings (e.g., Muldner et al., 2010) for a subset of the participants (since this is a laborious process that requires transcription and analysis of many fine-grained events), and (2) for obtaining affect information, the target system will intermittently ask students to report on their emotions (as in Arroyo et al., 2009). Note that these techniques are only necessary during model-testing – once the model is calibrated, the self-report prompts and talk-aloud protocol are removed. To use these data to assess model accuracy, we will transcribe the talk-aloud protocols and identify metacognitive and affective events, and then use these data in conjunction with the self-report data to compare against the corresponding submodel output.

Factors Influencing Creativity: While work in psychology has provided indications of how various attributes influence creativity, the technological context of this approach affords opportunities for investigating creativity beyond traditional settings. In particular, the PI's suite of sensors provides a unique chance for extending the community's knowledge on factors that influence creativity. Thus, we will rely on the EDM techniques we have used in the past (Muldner, Burleson, Van de Sande & VanLehn, 2011) and/or adopt additional ones as needed in order to mine the rich data set collected in this phase for factors influencing creativity. Specifically, relevant features will be extracted, e.g., affective states, productivity during problem solving, effort invested, and used as inputs to EDM techniques, e.g., Bayesian network parameter learning (Muldner et al., 2011) andlogistic regression (Cooper et al., 2009; Cooper et al., 2010). This will inform how various events contribute to creativity (e.g., a student reported frustration and this was related to a low creativity time span) and the relative utility of each event to the overall creativity process. We also plan to analyze the relative utility of each sensor (as we did for Muldner et al. [2010] and Cooper et al. [2010]) in order to understand which sensors are most valuable for creativity assessment as well as what the trade offs are when not all sensors are available.

Realizing Creativity Support within the GIFT architecture

As we have described above, ICS requires modeling of a range of student attributes, from domain knowledge, to meta-cognition, to affect. Aspects of the GIFT architecture are well aligned to support these modeling requirements. In particular, this architecture includes the *sensor module* that provides an interface for incorporating a range of sensing devices, which prior work has been shown to be useful for modeling affect (e.g., Arroyo et al., 2009). The input from these devices can then be sent to the GIFT *learner module* in order to map the low level sensor signals to the high level affective states of interest, like interest, frustration and/or flow – this module can also be used to assess students' domain knowledge and meta-cognitive skills. The GIFT *pedagogical modules* can rely on this information to tailor interventions in order to support and foster students' creativity.

GIFT also includes a *domain module*, that is used to structure and represent the target domain knowledge the student is expected to acquire – this is also relevant to creativity support, as students are expected to learn about the domain through creative activities. However, one aspect that is not clear and will need future exploration is how well the GIFT domain modules support the more open-ended domains that are required for creative endeavors, i.e., domains that afford users opportunities freedom to explore multiple solutions, apply divergent thinking and exhibit flexibility in their approaches. Many open-ended domains are ill defined in that it is difficult to specify objective criteria for solution evaluation – consequently we foresee this as one of the challenges in realizing creativity support in general and within the GIFT architecture in particular.

Conclusion

We have discussed the ICS framework and its application to the integration of ITS, affective computing, and CST to foster students' creativity. We have also outlined our research strategies for taking the next steps to implement and evaluate this approach, as well as initial considerations on how ICS can be realized within the GIFT architecture and challenges associated with doing so.

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